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Spatial Distribution of Soil Organic Carbon and Total Nitrogen in a Ramsar Wetland, Dafeng Milu National Nature Reserve

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Abstract: The invasion and expansion of *Spartina alterniflora* in coastal salt marsh wetlands have greatly affected the material cycle of the ecosystem. A total of 372 topsoil samples were collected from 124 sites representing two land-cover types by implementing an unprecedented high sampling density study in the Dafeng Milu National Nature Reserve. Classical statistics and geostatistics were used to quantify soil organic carbon (SOC) and total nitrogen (TN) spatial distribution. Redundancy analysis (RDA) was used to detect correlations between environmental factors, SOC, and TN. The results showed that SOC and TN have moderate variability. The spatial distributions of SOC and TN were similar, and the highest values were observed in the southwest of the study area. In different land cover types, the SOC and TN in the vegetation coverage areas with *Spartina alterniflora* as the dominant species were significantly higher than those in bare land. RDA showed that TN and aboveground biomass significantly affected the spatial distribution of SOC, while SOC and AGB dominated the spatial distribution of TN.

Keywords: Dafeng Milu National Nature Reserve; soil organic carbon; total nitrogen; geostatistics; redundancy analysis

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1. Introduction

Affected by the interaction of sea and land, coastal wetlands provide essential ecosystem services, including shoreline protection, biodiversity maintenance, and regional climate regulation [1–3]. The carbon stored in plants and soil of terrestrial ecosystems through photosynthesis is often called "green carbon". The carbon stored in ocean sinks, such as mangroves, marshes, and seagrasses, is referred to as "blue carbon" and accounts for more than 55% of green carbon [4,5]. In contrast to terrestrial green carbon and marine blue carbon, the carbon stored in coastal ecosystems is defined as "coastal blue carbon". In the "coastal blue carbon" ecosystem, soil is the largest carbon pool and provides an environment for wetland plant growth [6]. Most vegetation residues are accumulated in the wetland soil in soil organic matter, making the wetland soil play the role of "carbon sink" [3,7,8]. Wetland soil is an integral part of the nitrogen cycle, in which nitrogen content, migration, and transformation have an essential impact on the structure, function, and productivity of the entire wetland ecosystem [9]. Affected by soil physical, chemical, and biological processes, SOC and TN exhibit significant heterogeneity in spatial locations [10]. Therefore, studying the spatial distributions of SOC and TN can effectively reveal their spatial patterns and ecological processes, which is of great significance in understanding corresponding geochemical processes.

The horizontal and vertical spatial distribution of SOC and TN is affected by various factors, including natural and human factors. For example, climatic factors have a significant influence on the decomposition of soil organic matter and thus affect the content of TN [11]. Elevation (Ele) is closely related to the soil hydrology regimes, which affects the growth range of land cover, thus further affecting the spatial distribution of SOC and TN [12]. Soil physico-chemical properties, such as soil electrical conductivity (SEC), soil bulk density (SBD), pH and soil water content (SWC), affect SOC and TN by affecting soil enzymes, soil microorganisms, and other biological processes [13]. Furthermore, soil texture and land cover types are strongly linked to the distribution of SOC and TN, and the latter is the main factor controlling the vertical distribution of SOC and TN [14–16]. The composition and structure of soil minerals will also affect the storage and transfer of SOC and TN [17]. Factors related to anthropogenic activities, such as the artificial introduction of exotic plants, stocking of wild animals, and land management, can also increase the spatial heterogeneity of SOC and TN to varying degrees. In recent years, scholars have conducted a great deal of research on the formation process, natural environmental conditions, and ecosystem of the Yancheng coastal wetland. However, only a few studies have focused on the contribution of single environmental factors to SOC and TN [18,19]. In terms of sampling, most previous studies measured soil element reserves based on individual sampling points, and there was a lack of high-density sampling research. Therefore, studying the spatial distribution of SOC and TN in the Dafeng Milu National Nature Reserve (DMNNR) on a regional scale and quantitatively evaluating the impact of these environmental factors on SOC and TN is of great significance in understanding the transformation and accumulation of soil nutrient elements in coastal wetlands.

The Yancheng coastal wetland is China's largest muddy coastal wetland, a complete ecological model, and exhibits the most complex erosion and deposition evolution in the country [20]. To protect the coast, *Spartina alterniflora* (*S. alterniflora*) was introduced in the 1980s [21]. It is a perennial herb with wide salt tolerance, strong flooding tolerance, strong hypoxia tolerance, and a high reproductive coefficient [22,23]. The third core area of the DMNNR has been silted up in the last 20 years. The salt content of soil and water is approximately 3% year-round, which is especially suitable for the growth of *S. alterniflora*. Due to the lack of natural enemies, *S. alterniflora* spread rapidly in coastal mudflats, occupying a large area of bare land. Its distribution area accounts for 60% of the region's total area, becoming a single absolute dominant species and reducing wetland biodiversity. Therefore, the present study sought to answer two questions: first, whether there are significant differences in SOC and TN under different land cover ties in DMNNR and second, which environmental factors have the most powerful influence on the spatial distribution of SOC and TN.

2. Materials and Methods

2.1. Study Area

The selected study area is the DMNNR located in southeastern Dafeng, Yancheng City, Jiangsu Province, which exhibits an area of 25 km^2 (Figure 1). The land is flat, and the soil is silty, which belongs to coastal meadow-saline soil. The average annual temperature is approximately 14.1 °C and the average annual precipitation is 1068 mm, the number of annual rainfall days can reach 116.4 days [24]. *S. alterniflora* was introduced to the reserve in 1983 and has replaced the local species of *Phragmites australis* (*P. australis*) and *Suaeda glauca* as the dominant species for over 30 years.

2.2. Soil Sampling and Analysis Methods

Field sampling was conducted during the peak growing season (August) in 2020. Soil samples were collected from the depth of 0–20 cm with a measurement interval of 500 m. Trimble R8s RTK with 5 mm positioning accuracies and continuously operating reference stations (cors) (spatial reference: CGCS2000 120E) were used to recorded the geo-positioning and Ele of the sampling locations. Three 1 m × 1 m quadrats were randomly selected within 3 m radius of each site for sample collection, and a total of 372 soil samples (124 sites × 3 quadrats) were collected. Before collection, a ring knife with volume of 100 cm^3 was used collect soil cores to determine SBD and SWC. Three soil samples from each site were thoroughly mixed into one sample for soil physicochemical analysis. Due to the large collection workload, in order to avoid the direct comparability of samples affected by different weather or hydraulic conditions, the sampling work was controlled at the lowest tide level on 28 rainless days. After soil samples were air-dried, it passed through 10-mesh sieves to determine the soil pH and SEC, and then part of it passed 100-mesh sieves to analyze the content of SOC and TN. SBD and SWC were determined according to the methods compiled by Society of Soil Science of China [25]. Soil pH and SEC were measured using a pH meter and conductivity meter, respectively. SOC was measured using the standard wet oxidation method (Walkley–Black technique) [26]. TN concentrations were measured using an elemental analyzer in CNS mode (vario MACRO cube, Germany). In addition, the aboveground biomass (AGB) within 264 quadrats (88 sites × 3 quadrats) was collected, bagged, and oven-dried for 48 h to a constant weight at 80 °C.

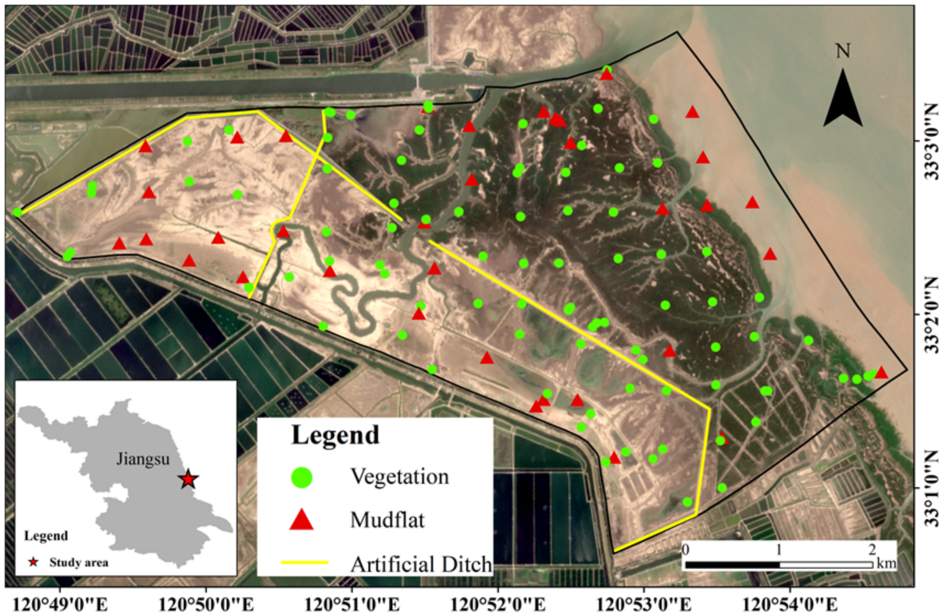

Figure 1. Locations of the study area and the sampling points of vegetation (n = 88) and mudflat (n = 36) in DMNNR.

2.3. Data Analysis

Because of the inherent spatial dependence between samples and the fact that traditional statistics can only reflect the overall characteristics of samples, it is difficult to describe their spatial correlation, structure, and randomness. Therefore, a combination of geostatistics and descriptive statistics was used to characterize the spatial variations in SOC and TN. Geostatistics [27] used a semi-variogram to quantify the uncertainty in estimating unmeasured values of regionalized variables. Semi-variance is an autocorrelation statistic defined as follows [28]:

$$\gamma(h) = [1/2N(h)] \sum_{i=1}^{i=N(h)} [Z(x_i) - Z(x_{i+h})]^2 \quad (1)$$

where $Z(x_i)$ and $Z(x_{i+h})$ are the values of the measured samples at the position x_i and x_{i+h}, and $N(h)$ is the total number of sample couples for the lag interval h.

We obtained the nugget variance, still, range and three theoretical models (i.e., Gaussian, spherical and exponential models) by fitting the semi-variograms. The spatial dependence of SOC and TN based on the nugget/still ratio was divided into distinct classes: if the ratio was >75%, the variable was considered weakly spatially dependent; if the ratio was between 25 and 75%, the variable was regarded as moderately spatially dependent; and if the ratio was ≤25%, the variable was regarded as strongly spatially dependent [29]. By selecting the model with the highest regression coefficient (R^2) and the smallest residuals sum of squares (RSS), the model parameters with high confidence are provided for the spatial interpolation of SOC and TN.

Ordinary Kriging (OK), as widely used in soil studies [12,30,31], is a univariate method of prediction as expressed by Equation (2):

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i),\ (i = 1, 2, \ldots, n) \tag{2}$$

where $\hat{Z}(x_0)$ is the value to be estimated at the unknown place of x_0, λ_i are the weighted values of measured x_i locations neighbouring x_0, which are predicted by the OK system. The OK method estimates the corresponding values (SOC and TN content in our case) of unknown locations through the linear weighted average of known adjacent data points. As such, since the weight λ_i are not arbitrary values, the OK method relies on soil carbon and nitrogen data only irrespective of the other environmental variables at that sampling site.

In variation analysis, we chose two-independent samples nonparametric test when any factor does not conform to a normal distribution. The Mann–Whitney *U* test was selected to compare the differences in SOC and TN contents between vegetation and mudflats. In the analysis process, the software has automatically standardized the data, and there were no outliers.

Redundancy analysis (RDA) explains the variation between the response variables (SOC and TN) and explanatory variables (environmental factors) using multiple linear regressions. In this study, RDA was performed using Canoco 5.0. Multiple linear regression (MLR) analysis, the Kolmogorov-Smirnov (K-S) test, and the Mann-Whitney U test were performed using SPSS 25.0. All geostatistical analyses were performed with GS^+ 9.0, and maps were produced using ArcGIS 10.3. The Pearson correlation analysis was conducted using OriginPro 2021b.

3. Results

3.1. Descriptive Statistics

The data were tested for normality before the geostatistical analysis. The square-root transformed data of SOC and TN exhibit smaller skewness (varying from 0.417 to −0.082 and 0.463 to 0.057). More significant kurtosis varied from −0.770 to −0.850 and −0.512 to −0.802. The square-root data passed the K-S normal distribution test at a significance level of $p > 0.05$.

Table 1 shows the summary of statistical parameters of soil physico-chemical factors. The median SOC (7.849 g/kg) was greater than the median TN (0.888 g/kg). The SOC changed considerably from 0.806 to 19.735 g/kg, whereas TN changed slightly from 0.228 to 2.116. Both SOC and TN presented a medium intensity variation, and CV was 55.601% and 44.416%, respectively, due to the different land-cover types.

We explored the spatial differences in SOC and TN with vegetation and mudflats. The results of the Mann–Whitney U test indicates that land cover significantly affected the content of SOC and TN ($p < 0.001$) (Table 2). The concentrations of SOC and TN in the vegetation area were higher than those in mudflat.

3.2. Spatial Distribution of SOC and TN Content

Acccording to the results of the semi-variance analysis (Table 3), the best fit for SOC and TN was the Gaussian model and spherical model, respectively. In general, the nugget/still ratio can reflect the spatial correlation of the system variables [32]. In our study, the nugget/still ratio showed a moderate spatial dependence for SOC and TN, which was influenced by inherent variations (i.e., soil characteristics) and extrinsic variations (animal activity and human practice). SOC (43.041%) had a stronger spatial correlation than that of TN (38.517%).

Table 1. Summary of statistical parameters of of soil physico-chemical factors.

Variables	Standard Deviation	Variation Coefficient	Minimum	25%	Median	75%	Maxima	Mean
SBD (g/cm^3)	0.197	16.256	0.723	1.069	1.229	1.376	1.623	1.213
pH	0.244	2.743	8.290	8.731	8.900	9.086	9.523	8.912
SEC (mS/cm)	1.387	50.583	0.191	1.692	2.775	3.761	6.117	2.743
Ele (m)	0.538	5.144	9.153	10.121	10.417	10.695	12.393	10.468
SMC (%)	8.445	16.530	26.707	44.838	50.560	57.127	76.617	51.087
SOC (g/kg)	4.767	55.601	0.806	4.690	7.849	12.203	19.735	8.574
TN (g/kg)	0.417	44.416	0.228	0.598	0.888	1.244	2.116	0.938
C/N	2.365	26.945	1.927	7.167	8.942	10.382	14.054	8.777
AGB	1041.110	69.497	17.250	530.271	1232.500	2331.125	3872.750	1498.060

Note: SBD = soil bulk density, SEC = soil electrical conductivit, SMC = soil moisture content, Ele = elevation, AGB = aboveground biomass.

Table 2. Results of Mann–Whitney U test of SOC and TN contents under different land over types.

		25%	Median	75%	Z	*p*
SOC (g/kg)	vegetation	7.537	10.464	13.251	−6.600	0.000
	mudflat	2.287	4.136	5.582		
TN (g/kg)	vegetation	0.792	1.085	1.365	−5.780	0.000
	mudflat	0.442	0.572	0.739		

Table 3. Geostatistical parameters of SqrtSOC and SqrtTN in different models.

	Model	Nugget	Still	Range (m)	Nugget/Still (%)	R^2	RSS
SqrtSOC	Gaussian model	0.334	0.776	693	43.041	0.902	2.37×10^{-2}
	Spherical model	0.260	0.775	805	33.548	0.902	2.39×10^{-2}
	Exponential model	0.140	0.778	780	17.995	0.861	3.39×10^{-2}
SqrtTN	Spherical model	0.020	0.051	1150	38.517	0.905	1.18×10^{-4}
	Gaussian model	0.024	0.051	953	46.107	0.897	1.28×10^{-4}
	Exponential model	0.011	0.052	1110	22.008	0.882	1.48×10^{-4}

Note: R^2, regression coefficient; RSS, residual sums of squares.

Based on the experimental semivariogram of the best-fit models, the maps were used to visualize the spatial distribution of SOC and TN with OK method (Figure 2). There were similar distributions of SOC and TN in DMNNR, with the highest values occurring in the west, middle, and south of the study area. In general, the SOC and TN values were higher in the southwest than in other parts of the study area, where *S. alterniflora* dominates the land mass [24].

3.3. Relationship between SOC and TN and Environmental Factors

Normally distributed test was conducted for all data, in which the data of SOC, TN and AGB have square-root transformation, and the data of Ele has reciprocal conversion. Figure 3 shows the result of correlation analysis between environmental factors and SOC and TN. There was a significant positive correlation between SOC and TN, AGB, SMC and C/N at the 0.001 level. Among them, there was a strong correlation between SOC and TN (r = 0.926), a medium correlation between SOC and C/N (r = 0.674), and a low correlation between SOC and AGB (r = 0.445) and SMC (r = 0.360). The significant positive correlation also existed between SOC and SEC at the level of 0.05, but the correlation was very weak (r = 0.177). However, SBD, pH were significantly negative correlated with SOC at the level of 0.001, and the medium correlation coefficients were −0.771 and −0.568 respectively. For other impact factors, Ele had no significant correlation with the SOC and TN ($p > 0.05$).

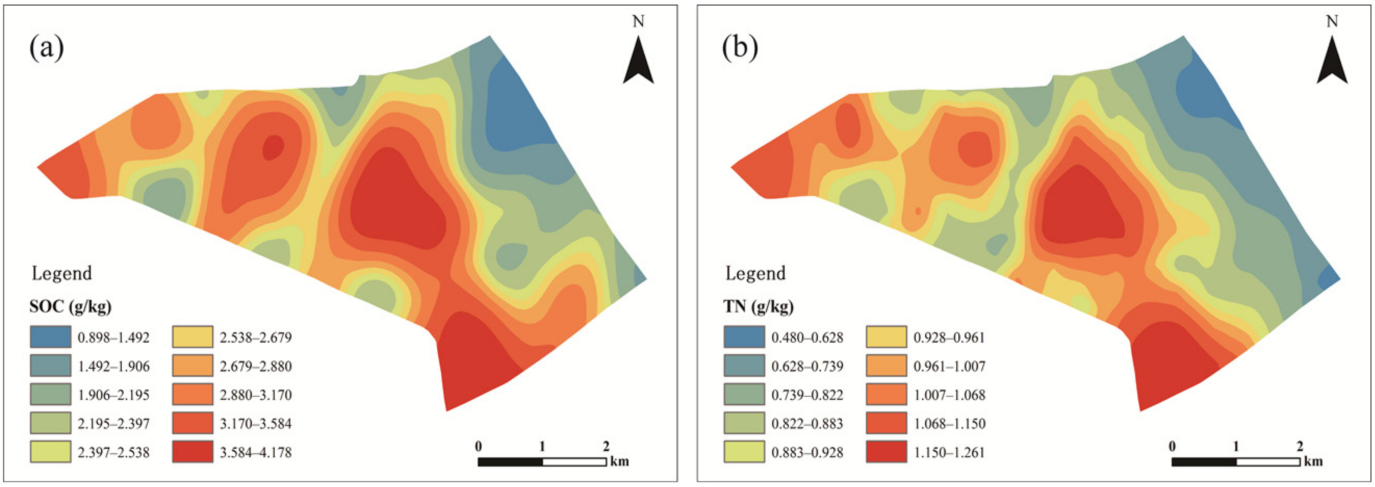

Figure 2. (**a**) Spatial distribution of soil organic carbon (SOC). (**b**) Spatial distribution of total nitrogen (TN).

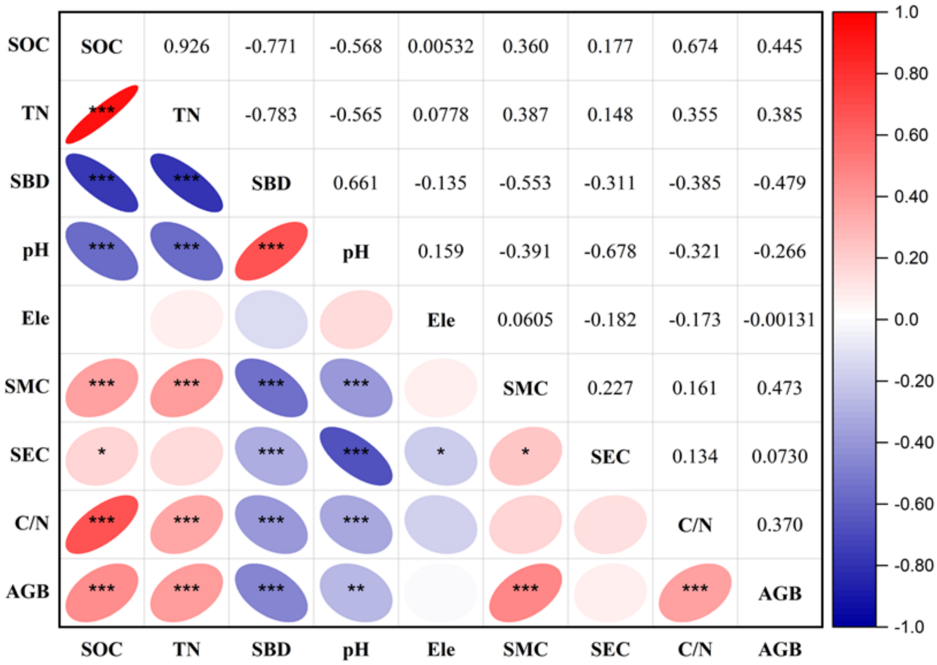

Figure 3. Pearson correlation between environmental factors and soil organic carbon (SOC) and total nitrogen (TN) (Note: red indicates positive correlations, blue indicates negative correlations; "*" indicates the significance correlation at $p < 0.05$, "**" indicates the significance correlation at $p < 0.01$, "***" indicates the significance correlation at $p < 0.001$, and the degree of concentration of ellipse indicates the strength of the correlation; the numbers indicate the correlation degree between variables; SBD = soil bulk density, Ele = elevation, SEC = soil electrical conductivit, SMC = soil moisture content, AGB = aboveground biomass).

RDA examines the relationship between a set of response variables and a set of explanatory variables by measuring the portion of the variance in the response variables, which is explained by explanatory variables. These calculations were performed within the iterative procedure, and the correlation coefficients between variables were displayed in the final dataset [33,34]. As strong collinearity can increase the degree of regression coefficients distribution in linear regression models [35], it is necessary to use MLR analysis to assess the collinearity of the explanatory variables. According to a previous analysis, a variance inflation factor (VIF) > 10 indicates collinearity between environmental factors. The results in Table 4 shows that all variables passed the multicollinearity test.

Table 4. Multicollinearity test among the environmental factors.

Factors		TN	SBD	pH	Ele	SMC	SEC	AGB	C/N
Collinearity Statistics	Tolerance	0.226	0.215	0.271	0.815	0.629	0.433	0.633	0.345
	VIF	4.423	4.654	3.693	1.227	1.589	2.308	1.580	2.901

Note: SBD = soil bulk density, Ele = elevation, SMC = soil moisture content, SEC = soil electrical conductivity, AGB = aboveground biomass.

The environmental factors explained 72.800% of the variation in SOC in the study area, in which TN, AGB, and C/N accounted for 71.500%, 16.100%, and 10.500% of the total interpretation, respectively, and pH accounted for 1.400%. Furthermore, environmental factors explained 74.600% of the variation in TN, with SOC, AGB, and C/N accounting for 77.700%, 13.700%, and 6.900% of the total interpretation, respectively. For all predictors, the p-values were lower than 0.05, demonstrating the excellent prediction capability of the model.

4. Discussion

4.1. Effects of Land Cover Types on SOC and TN

This study found that the contents of SOC and TN in the vegetation area dominated by *S. alterniflora* were significantly higher than those in the mudflat (Table 2), which is consistent with previous research [18,20]. Generally, there are two primary sources of SOC in coastal wetlands: one is the terrestrial source, which is mainly provided by animals and plants; the other is the marine source, which is mainly produced by plankton and benthos in the sea [36]. In areas strongly affected by human activities, some human inputs will be included such as urban domestic, and industrial sewage discharge as well as chemical fertilizers and pesticides used in agricultural production [18]. However, in our study area, DMNNR is mainly responsible for the restoration of *Elaphurus davidianus* (*E. davidianus*) population and the protection of coastal wetland ecosystem, with few human production and life activities. Many scholars have found that *S. alterniflora* in coastal wetlands could increase soil carbon storage by increasing primary productivity and litter decomposition rate. Meanwhile, the SOC content in bare flats is lower than that in vegetation regions due to the lack of vegetation cover and the influence of tides [37]. TN mainly affects SOC by controlling the mineralization rate of organic matter and vegetation growth [38]. The TN content showed a spatial pattern similar to that of the SOC content (Figure 2). The TN storage tends to increase remarkably with the input of vegetation and the nitrogen fixation effect of microorganisms [39]. As demonstrated in previous research, the TN content in the vegetation region was significantly greater than that in the mudflat (Table 2) [37,40]. The bare flat, which was mainly affected by the tide, had a weak interception capacity for nitrogen. In addition to the abundant carbon source provided by the aboveground vegetation for soil microorganisms, the well-developed roots in the underground also provide a favorable survival environment for nitrogen-fixing microorganisms in the soil [41].

4.2. Effects of Environmental Factors on SOC and TN

The results of RDA showed that among all environmental factors, the influence of SOC and TN on each other was the most dominant factor explaining their spatial changes. AGB was the secondary factor explaining the spatial changes in SOC and TN (Figure 4). There is a coupling relationship between the carbon and nitrogen cycle. On the one hand, nitrogen in wetland soil mainly originates from atmospheric deposition, tidal transport, and plant litter input. Soil nitrogen concentration and storage could significantly affect aboveground plants, which are the significant sources of SOC [39,42]. On the other hand, SOC, TN, and AGB interacted with each other. The input of carbon and nitrogen in soil could improve the AGB. The increase in AGB could input more organic matter into the soil and increase the content of SOC and TN [43]. Soil microorganisms maintain their fixed stoichiometric ratio by inducing and maintaining decomposed and transformed materials in the soil [44]. Soil C:N ratio can be used as an index to indicate the decomposition rate of SOC, and the high C:N ratios (>25) indicate that the decomposition rate of SOC is becoming slower [45]. The soil C:N ratio was 8.777 (Table 1) in the study area, thereby indicating a moderate rate of SOC decomposition; supporting the results of Gao et al. [18].

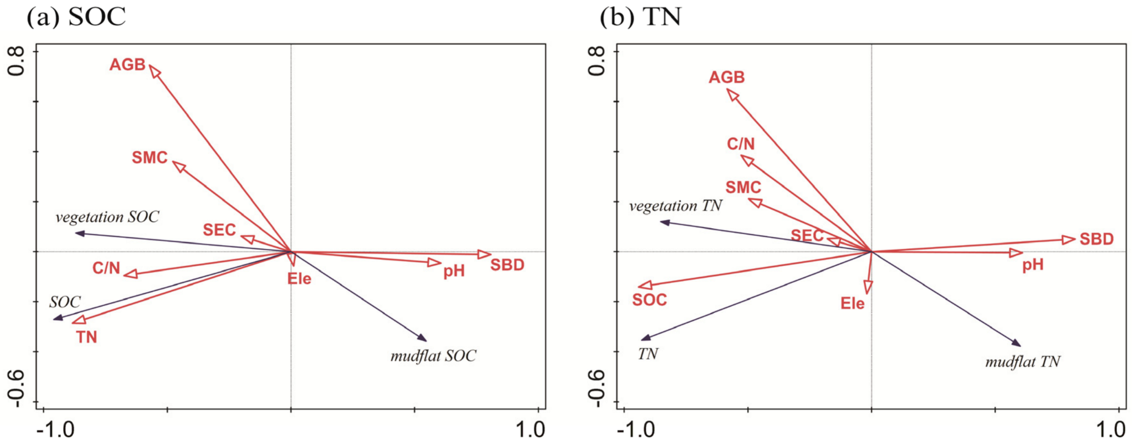

Figure 4. RDA of the relationship between environmental factors and soil organic carbon (SOC) (**a**), and total nitrogen (TN) (**b**) under different land cover types (Note: blue lines indicate the response variables and red lines indicate explanatory variables; SBD = soil bulk density, Ele = elevation, SEC = soil electrical conductivity, SMC = soil moisture content, AGB = aboveground biomass).

SBD is closely related to SOC in wetland [46]. SBD affects SOC by limiting plant root growth, litter decomposition and microbial activity. In this study, there was a negative linear correlation between SBD and SOC (Figure 3), which was consistent with the existing research conclusions [47]. In addition, microorganisms can be promoted or inhibited by soil pH. Their activity is the largest (6–8), which impacts the spatial distributions of SOC and TN in coastal ecosystem [36,41]. The Pearson correlation analysis and RDA revealed the significant impact between soil pH values and SOC and TN (Figures 3 and 4). However, the average soil pH value was 8.912 (Table 1), indicating that the microorganisms were still in the dynamic range and affected the contents and spatial distributions of SOC and TN in DMNNR.

In contrast to previous research results, Hu et al. [12] proved that the content and distribution of SOC and TN showed a significant positive correlated with Ele at the level of 0.01. However, the difference in Ele between the sample points in the study area was only 3.240 m (Table 1). The interpretation of SOC and TN in RDA was less than 1%. Therefore, Ele was not the main environmental factor affecting the content and distribution of SOC and TN in our study. Different conclusions have been established regarding the relationship between SOC, TN, and SWC in different studies. Chen [37] studied Chongming wetlands and found a negative correlation between carbon and nitrogen storage and SWC. However, in our study, the results of correlation analysis showed that high moisture content would increase the contents of SOC and TN (Figure 3). However, the explanation of SWC for the spatial distribution of SOC and TN content is less than 1% in RDA, which may be due to the influence of periodic flooding on vegetation and mudflats. The change in SWC could also affect SEC, which influences the activities of soil microorganisms and changes the turnover rate of SOC [42,48].

4.3. Other Factor in the Spatial Distribution of SOC and TN

In the RDA, environmental factors explained more than 70% of the spatial changes in SOC and TN in DMNNR. Approximately 30% of the changes remain unexplained due to the lack of basic soil properties such as soil texture, soil temperature, and the composition, structure, properties of soil minerals. Under similar climatic conditions, soils with a finer particle size distribution can bind the aggregated SOC content, thereby delaying the decomposition process of organic carbon [49]. Furthermore, many tiny pores in the fine-structured soil reduce the decomposition of organic matter by microorganisms [50]. In previous studies, soil temperature was the main environmental factor affecting CH_4 and N_2O fluxes in swamp wetlands with periodic tides [51,52]. An increase in soil temperature can increase the decomposition rate of soil organic matter by soil microorganisms [53]. In addition to environmental variables, the artificial ditches (Figure 1) organized and constructed by the reserve and the trampling and consumption of plants by *E. davidianus* will also influence the growth of vegetation, thereby affecting the spatial heterogeneity of soil carbon and nitrogen. The construction of artificial ditches cut off the hydrological connectivity between *S. alterniflora*, resulting in the dynamic succession of vegetation in the reserve. Since the introduction of *E. davidianus* in the reserve in 1986, with the increase of population density, *E. davidianus* has repeatedly gnawed and trampled on the surface favorite vegetation (such as *S. alterniflora*, *P. australis*, *Imperata cylindrica*, etc.), which has seriously affected the growth of vegetation [54], led to the gradual disappearance of some species in *E. davidianus* habitat, and made the trend of vegetation simplification in tidal flat.

5. Conclusions

This study analyzed the spatial distribution and contribution of influencing factors on the SOC and TN content in the DMNNR. The medians of SOC and TN were 7.849 g/kg and 0.888 g/kg, respectively, which showed medium intensity variation throughout the study area. The land cover significantly affected the content of SOC and TN, and the concentrations of SOC and TN in the vegetation area were higher than those in the mudflat. The invasion of *S. alterniflora* has imortant limplications to the accumulation of soil carbon and nitrogen in coastal wetland ecosystem. The results of geostatistical analysis showed that the Gaussian and spherical models were best for predicting SOC and TN, respectively. In the topsoil, SOC and TN exhibit a medium spatial dependence, and the highest SOC and TN contents are distributed mainly in the southwestern part of the study area. SOC has significant linear correlation with other environmental factors in varying degrees, except for Ele. The RDA results showed that TN and AGB were the controlling factors affecting SOC, while SOC and AGB were the main environmental factors affecting the spatial heterogeneity of TN. The invasion of *S. alterniflora* changed the distribution pattern of soil carbon and nitrogen pools in coastal wetlands. These results can supplement and improve the data accuracy of soil carbon and nitrogen pools of coastal wetlands in China and provide a theoretical basis and decision support for ecological function evaluation and management of coastal wetlands.

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